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ADAPTIVE GMM FOR MULTIPLE OBJECTS TRACKING WITH OCCLUSION HANDLING

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ABSTRACT: Object tracking is an important activity in an intelligent video surveillance system. The most common approach to tack objects is to first detect them by using background subtraction technique. Per-pixel adaptive Gaussian Mixture Models (GMMs) have become a widely accepted choice for the detection of change in the video surveillance domain because of their ability to achieve most of the requirements of a surveillance system in real-time with low memory requirements. Per pixel GMM can be further improved with a variance controlling scheme and the incorporation of region analysis-based feedback. Occlusion makes object detection and tracking a difficult problem, especially in case of multiple moving objects. This paper proposes a competent framework which can detect and track the moving objects without a priori knowledge of objects in the scene, detects occlusion by Improved Mean Shift Tracking (IMST) algorithm and handle occlusion by Frame Matching (FM).
Keywords: Background subtraction, GMM, IMST, FM, Occlusion.

I. INTRODUCTION

Surveillance is act of monitoring the behavior, activities, or other changing information, for influencing, managing, directing, or protecting them. One of the main advantages of video surveillance is that it could be used for a prevention and a forensic purposes for crimes. Visual surveillance system is used to detect, recognize, and track certain objects in a scene. This type of system was mainly used in applications such as security for human, important building, military target detection and traffic surveillance in cities. Object tracking is an essential component of an intelligent video surveillance system. Object tracking is a process that follows an object through consecutive frames of images to determine the object's motion relative other objects of those frames. More accurate and real-time object tracking will significantly improve the performance of object recognition and high level event understanding.

In the surveillance domain, change detection has been extensively used in order to segment foreground objects from the background. Foreground objects are objects that are associated between frames in order to perform a scene analysis and detect events of interest. The scenes which are normally observed are considered as background. Therefore, the background can be well depicted by means of a statistical model, the background model. There are many challenges like video noise, ghost, left object, uncertainty camera shaking, and sudden illumination changes which make background modeling difficult.

Per pixel Gaussian Mixture Models (GMMs) have become a widely choice for the detection of change in the video surveillance domain because of their ability to deal effectively with many challenges characteristic for surveillance systems in real time with low memory requirements. Basically, the history of each pixel is modeled by a mixture of *K* Gaussian distributions, which are then updated by means of an Expectation Maximization (EM) algorithm. Based on this model, pixels are classified as either background or foreground. Per pixel GMM can be further improved by means of a variance controlling scheme and the incorporation of region analysis-based feedback.

Variance controlling scheme, which aims to adaptively compute an appropriate value for the initialization of the variance parameter of new modes and to control the variance of existing modes so as to avoid a degeneration of the model. Furthermore, segmentation results are improved by means of incorporating region-level analysis information into the background model. To that aim, two-layered system has been used which analyzes each frame of a video sequence at two levels: at the pixel level, pixels are classified according to the results obtained by the subtraction of two complementary background models; at the region level, new static foreground regions are classified as static or removed objects. This classification information is feedback to the pixel level in order to avoid the incorporation of static foreground objects into the background model, while allowing a fast healing of uncovered background regions.

The main application in mind of the proposed system is the detection of foreground objects in surveillance applications, whereby special attention has been paid to the generality of the proposed method for a wide range of scenarios (indoor, outdoor, different illumination conditions...), and to the problem posed by new and removed static objects.

Occlusion is hiding of an object by another object during multiple human tracking .An occlusion is the region between two overlapping objects that are in motion. Detecting these occluded objects is crucial for many of the video processing. Occlusion make the robust object detection and tracking a difficult problem, especially in case of multiple moving objects. Maintenance of the history of objects before and after occlusions is in multiple object tracking. An Improved Mean Shift Tracking algorithm (IMST) is used for occlusion target tracking. Occlusion detection is done by calculating the distance between center of mass and comparing it. If the difference is zero, it concludes that the objects are occluded. Occlusion handling is done by comparing the occluded part of a frame with the part of the similar previous frames and the occluded part is filled with the matched part of that object.

II. PROPOSED SYSTEM

This paper introduces a multiple objects tracking system, which detects and tracks multiple objects in crowded scene and also detects and handle occlusion. This system consists of

1) Getting input video
2) Conversion of video into frames
3) Prepossessing of individual frames
4) Object detection and Foreground object extraction
5) Object tracking
6) Occlusion detection
7) Occlusion handling
8) Displaying objects

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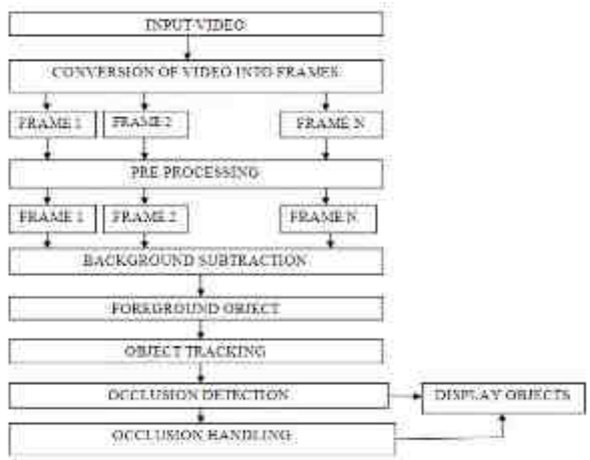

Figure 1: System architecture

1. FRAME GRABBER

Frame grabber is used for conversion of video into frames.

Steps are:

- Get video location from user
- Read the video from that location
- Calculate the length of video
- Captured video is converted into frames until end of the frame

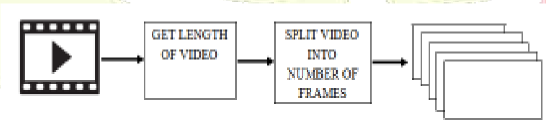

Figure 2: Frame grabber

2. PREPROCESSING

Pre-processing is to improve the results of later processing. It mainly involves filtering process. This can be done with use of Gaussian filter. Gaussian filtering is used to blur images and remove noise in order to achieve high accuracy for detecting the moving objects.

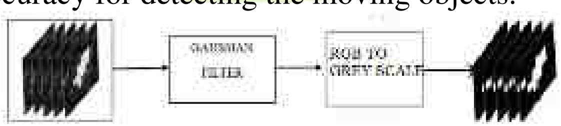

Figure 3: Preprocessing

Grayscale image is used in entire process instead of the color image to reduce processing time. The grayscale image is an image that has one color channel which consists of 8 bits while RGB image has three color channels.

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3. OBJECT SEGMENTATION

Image segmentation is splitting of digital image into multiple segments (sets of pixels, also known as super pixels). Segmentation is to simplify portrayal of an image into something which is more meaningful and easier to analyze. Image's foreground is extracted for further processing by Background Subtraction technique.

Background subtraction (Foreground Detection) is a technique where image's foreground is extracted for further processing (object recognition or tracking). Generally foreground objects in an image are objects that are an image's regions of interest (humans, cars, text etc.). After image preprocessing, object localization is required which may makes use of this technique. Background subtraction is a popular approach for detecting moving objects in videos from static cameras. The principle of this approach is detecting the moving objects from the difference between the current frame and a reference frame, called "background model".

Gaussian Mixture Model (GMM) is used for constructing background model. In this technique, it is assumed that every pixel's intensity values in sequence of frames can be modeled using GMM. Then the pixels which do not match to these are foreground pixels. Foreground pixels are grouped using connected component analysis. Thereby, the history of each pixel is modeled by a mixture of *K* Gaussian distributions. This model is used to estimate the probability of observing a given pixel value *Xt* at time *t* as:

$P(Xt) = \sum \omega_k N(X_t, \mu_k, \sum_k)$

Where ω_k are the weights associated to each of the modes $k \in \{1 \ldots K\}$ describing a pixel

$N(X_t, \mu_k, \sum_k)$ is a normal density of mean μ_k and covariance matrix $\sum_k$

BS involves 2 steps: background initialization and background maintenance.

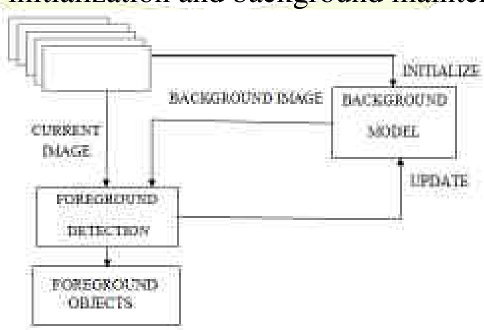

Figure 4: Object segmentation

i) Background Initialization

At system start, the GMM for each pixel has to be initialized. To that aim, the observed value at each pixel is used as its mean value for the initialization of the variance parameter. Each GMM is initialized with a unique mode, which describes the background of the scene at this point in time. The variance term of each mode accounts for the variation of the values corresponding to the given distribution.

Correctly initializing this parameter is of crucial importance since it has a significant implication on the behavior of the system. A too low value may lead the system to generate several modes to statistically describe a unique on time distribution, therefore over-fitting some boundary of the feature space. On the other hand, a too large value may lead the model to accommodate samples from different distributions into a unique mode, therefore under-fitting the underlying multi-modal distribution. For the estimation of the variance parameter, we use pairs of consecutive video frames and compute for each pixel the deviation from the first to the second frame.

ii) Background Maintenance

After the initialization period of the background model, for every new frame, the observed pixel value *Xt* at each pixel position is compared against its corresponding GMM so as to classify the pixel as foreground or background, and to iteratively adapt the GMM to the described on-time distribution.

For this purpose of background updating, Background maintenance algorithm is used which involves Region analysis feedback. Here it analyzes each frame at 2 levels: pixel level and region level. At the pixel level, pixels are classified according to the results obtained by the subtraction of two complementary background models; at the region level, new static foreground regions are classified or categorized as static or removed objects. This classification information is fed back to the pixel level in order to avoid the incorporation of static foreground objects into the background model, while allowing a fast healing of uncovered background regions. This improves segmentation results and avoids incorporation of static foreground into background. Also information obtained from region analysis is used as updating scheme of background model.

4. OBJECT TRACKING

Object tracking aims to establish a correspondence between objects or object parts in consecutive frames and to extract temporal information about objects such as speed and direction. Tracking detected objects frame by frame in video is a significant and difficult task.

Object tracking is done by comparing the previous image and current image using absolute difference method by Sum of Absolute Differences (SAD) algorithm. It works by taking the absolute difference between each pixel in the original block and the corresponding pixel in the block that is being used for comparison. These differences are added to create a metric of block similarity.

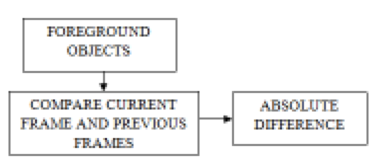

Figure 5: Object tracking

5. OCCLUSION DETECTION

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Occlusion detection is done by calculating the distance between the center of mass of two objects in a frame. Then occlusion will be detected when the distance is nearly zero. There are two modules in occlusion detection.

- Object separation from each frame.
- Centre of mass calculation of each object.

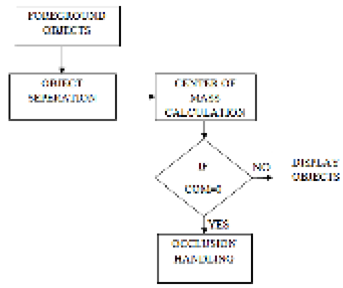

Figure 6: Occlusion detection

6. OCCLUSION HANDLING

The occluded frame is identified by Improved Mean Shift tracking algorithm. The occluded part is detected by finding center of mass of occluded object. Using the Frame Matching (FM), the occluded part is then matched with the preceding frames to find the correct match of the missing part.

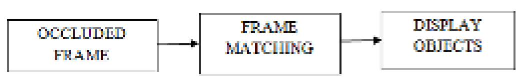

Figure 7: Occlusion handling

III. CONCLUSION

This approach presents a multiple object tracking system with occlusion handling. It includes an enhanced GMM method for the task of background subtraction to detect regions that belonging to static foreground regions or uncovered background regions. The information provided by the region analysis layer is then fed-back to the pixel layer .The major advantage of the system is its ability to hold static foreground regions in the foreground and correctly incorporating into the background model. The classification of static foreground regions is the key for the good performance provided by the system. The proposed method works well for a wide range of scenarios (indoor, outdoor, different illumination conditions...).In the proposed work, occlusion detection is done by calculating the distance between center of mass and comparing it. If the difference is zero, it concludes that the objects are occluded. Occlusion handling is done by comparing the occluded part of a frame with the part of the similar previous frames and the occluded part is filled with the matched part of that object. The proposed system will work not only on partial occlusions, but also work effectively on full occlusions.

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